International Journal of Emerging Engineering and Technology (IJEET)
ISSN (e): 2958-3764
Volume: 1, Number: 2, Pages: 24 - 29, Year: 2022

Dates Ripen State Identification Deep Learning Technique

Jawaid Shabbir, M. Usama, A. Ali, T. Hussain and M. Mazhar Khan

Computer Engineering Department, Sir Syed University Of Engineering and Technology Karachi, Pakistan
Corresponding author: Asghar Ali (e-mail: asgharali3930@gmail.com)

Received: 07/07/2022, Revised: 29/11/2022, Accepted: 13/12/2022

***Abstract*- One of the primary factors is that conventional approaches are expensive and time-consuming. An automatic system for classifying the maturity of palm dates was created in this suggested system to identify the various phases of date fruit ripeness quickly and accurately. The three stages of our system's operation are the one-stage deep learning model (You Only Look Once Yolov4) algorithm used to identify palm dates in a video frame, the centroid tracking algorithm used to keep track of each vehicle within a defined area of interest, and palm date ripen state detection algorithm. While the centroid tracking technique can effectively follow any moving item, the deep learning model (You Only Look Once Yolov4) approach is particularly accurate at detecting objects. A test using a few traffic movies demonstrates that our suggested approach can detect and identify any ripen state detection of dates in various lighting and weather scenarios. The technology is straightforward to use and put into place.**

***Index Terms*— YOLO, deep learning, dates.**

I. INTRODUCTION

Many people who rely on the date palm, known as "Khajoor" in Urdu, refer to it as the "tree of divine providence." As shown in Fig. 1, date palm trees assist populations in rural and desert oases in various ways. Dates have long been used as a source of high-energy nourishment by travellers across the desert. Dates are best suited for exporting and year-round eating since they are collected and sold as fresh, ripe yields at four different phases of improvement: immature, Khalal, Rutab, and Tamar. According to figure 2, the physical characteristics of a Date can be used to determine maturity.

However, the conventional approach is expensive and time-consuming. An automatic system for classifying the maturity of palm dates was created in this suggested system to identify the various phases of date fruit ripeness quickly and accurately. You Only Look Once V4, a cutting-edge deep learning technique with good long-distance object detection was developed and used to identify dates at various stages of development. Using the same deep learning image processing technique, fruit images were acquired from the air, on the ground, and in proximity. Therefore, photographs from unmanned aerial vehicles (UAVs) and photos from close-up digital cameras were categorized into four maturity phases.

Automatic date classification with maturity analysis in a natural setting is difficult for traditional vision tasks because different dates have different sizes, shapes, colours, and textures; unstructured orchard scenes have a high level of uncertainty; harsh occlusions; and highly variable lighting and shadow states. But due to several factors, these duties are more difficult with date fruits.

First, date orchards typically contain a wide variety of dates, many of which share striking visual similarities. In the same orchard, different date kinds are collected at various stages of maturity. Third, labelling or categorizing date bunches into a particular maturity class might be challenging since individual dates within a bunch typically mature at different rates (i.e., a date bunch typically contains individual dates at various maturity stages). Fourth, date bunches might be placed inside net bags, which would change how they look. We propose a robust deep learning-based machine vision system for categorizing the ripening condition of date fruit in various environments to address these difficulties. The framework uses four classification models to group images of dates in real-time according to the type, maturity, and harvest method.

The one-stage deep learning model is to be applied in classification models. We use a one stage deep learning model to combine transfer learning with fine tuning. Dates with flaws should be identified and categorized as soon as possible to decrease farmer duties and help preserve market food qualities even during date packing. This system focuses on preprocessing, feature engineering, Simple Deployment: Building a web service for prediction is the easiest approach to deploying a one-stage deep learning model. The model is simple to deploy to a device, and an outsider cannot meddle with its runtime environment. The requirement for the gadget to have adequate processing speed and storage space is undoubtedly a negative.

Model Monitoring: Model monitoring is a functional stage following model deployment in machine learning. It entails keeping an eye out for changes in your machine learning (ML) models, such as model deterioration, data drift, and concept drift, and ensuring that your model is still operating at an acceptable level.

II. LITERATURE REVIEW

Bazi et al. [1-5] gave a method for counting palm trees based on extracting a set of key point scale-invariant feature transform (SIFT). These critical spots are then examined using an active contour approach and an extreme learning machine (ELM) classifier that has already been trained. Finally, palm trees are distinguished from other vegetation types using local binary patterns (LBPs). However, they only used UAV images of 185 palm trees for testing their technique, and they got an average accuracy of 92%. Authors in [6-10] presented the first work in 2016 that used deep learning to recognize and count palm palms in multispectral Quick Bird satellite pictures.

Other research has employed harvesting robots to describe robotics and machine vision applications in agriculture. These fruit-picking robots can also locate fruit-bearing branches [8] and pick up fruit [11-17]. An algorithm for detecting objects was created in a different study [9] using data on colour, depth, and shape. Chen et al. [10] designed a multi-camera system for agricultural applications to broaden the scope of vision systems' perceptual capabilities. There have been numerous studies to categorize date fruits. To categorize three mature phases (Khalal, Rutab, and Tamar) and one faulty stage, Nasiri et al. [11] used computer vision and machine learning techniques.

A homogeneous background and single dates were used to create the dataset. The VGG-16 architectural model with max pooling, dropout, batch normalization, and dense layers was employed in this work. They used a smartphone to collect the dataset, and their algorithm had a 96.98% overall accuracy rate. Altaheri et al. [12] conducted a different investigation and suggested a framework for classifying date fruits in an orchard setting using a vision system. Using the suggested framework, they categorized photos of dates fruits according to type and maturity. Using the VGG-16 and Alexnet architectural models, this study could classify types with an accuracy rate of 99.01% and maturity classes with a rate of 97.25.

Similar goals drive the current work, but we take higher-resolution UAV photos into account. We use cutting-edge deep-learning object detectors in place of satellite photos instead of using conventional image processing methods. Other studies have considered different tree species. For example, [14] constructed a deep-learning model for identifying banana trees from aerial photographs. On Orth mosaic maps, they used a deep learning detection technique (Faster R-CNN with a 42-layered Inception-v2 [15] feature extractor). For heights of 40, 50, and 60 m, respectively, they achieved accuracy values of 96.4%, 85.1%, and 75.8% on the same farm. Our technique advances previous research since it can be used with geotagged photos, allowing us to accurately handle the problem of overlapping images and individually identify each palm tree by its geolocation. Other fruit classification studies besides dates have been conducted. Two ML-based algorithms for categorizing papaya fruit maturation phases were introduced in 2020 by Behera et al. [14] 300 papaya fruit photos were used, 100 of which represented each of the three stages of maturity.

In YOLO-V3, the method initially enhances a dense network structure before enhancing non-maximum suppression. The redesigned a priori box is, therefore, better suited for tomato detection. The YOLO-V3 algorithm is compared to the experiment. Tomato detection is improved with the YOLO-V3 [18]. With the help of preprocessing and post-processing, Anna Kuznetsova et al. successfully completed the robot detection test, allowing the YOLO-V3 algorithm to be employed in apple detecting and greatly facilitating robot harvesting. According to experiments [19], the algorithm has a low error rate and can reduce the normal detection time. As a result of the YOLO-V4 model's introduction [20], the identification of concealed objects is now more accurate. Dihua Wu et al. decreased the apple identification model and trimmed the channels on the YOLO-V4 camera to increase detection effectiveness. When compared to other methods such as Faster R-CNN, YOLO- V2, and YOLO-V3, it has been shown that the YOLO-V4 model performs better and can accomplish real-time and precise recognition of apple blooms [21].

Typically, a fruit's maturity index tells you when it's time to harvest that specific fruit. Nevertheless, several factors must be considered while choosing when to harvest date fruits.

- First, dates mature unevenly within a bunch because they grow in bunches.
- Second, there are numerous ways to harvest dates.
- The entire bunch is cut when most of them are ready, or ripe dates are chosen and picked.
- Third, different maturation stages of dates are harvested (Khalal, Rutab, and Tamar). Based on these criteria, we divided the date bunches into seven groups (phases): Immature (Khalal, Rutab, and Tamar) are all immature types.
- These maturity classes are determined by the texture and colour of the dates and the choices and methods for harvesting that have been discussed by experts and farmers, as indicated in the bar graph.
- As a result, throughout this essay, "maturity phases" refers to the level of ripeness of date fruits (immature, Khalal, Rutab, and Tamar).

III. METHODOLOGY

Transfer learning enables YOLO to function well even in visual classification problems with small or insufficient datasets [22-25]. The YOLO employed in transfer learning and one-tuning procedures rather than generating weight values at random [26]. The best techniques for transfer learning with one-tuning were covered in the study [27]. Using relatively limited datasets, like the one utilized in this work, it is difficult to learn these parameters from scratch. Overfitting occurs when YOLO networks find it easy to learn from little datasets, as shown in Fig. 3. Transfer knowledge was therefore employed in this research to prevent overfitting. The dataset size was also enhanced by applying randomly selected values for image growth on the training datasets [28].

During the training phase, a random selection was made for the date photographs in each batch. In addition to a-tuning, we applied transfer learning. Except for the last fully connected layer, all layers of the YOLO models' weights were learned using transferred data throughout the one-tuning process. The knowledge rates of the novel layer were boosted compared to the rest of the YOLO model, and its weights were initialized with random numbers. In one-tuning, learning rates for new layers rise while falling for initial layers. The YOLO model is only considerably changed due to the weights' better performance utilizing a large dataset and the need for modest tweaks. However, the additional coatings alteration their weights and catch on much more quickly. With a 0.5 probability, we introduced dropout layers after the two worst completely.

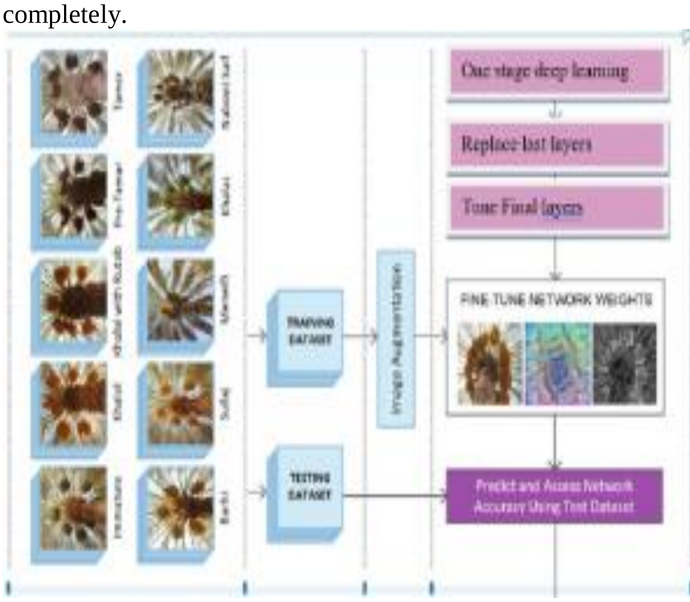

Figure 1: Typical diagram of the process.

A comprehensive image collection comprising 3000 photographs of extra than 360 date groups from 20 different date palms in different weather environments and illumination was developed to create a reliable vision system. These sessions discussed the intermediate stages (i.e., the changeover between the ripeness stages). Since there were a lot of variances in the dataset, it accurately reflects the difficulties faced by date fruit farms and the natural world.

Varying angles and scales, various lighting conditions (such as dimly lit photographs), date bunches covered by bags, and different daylight conditions were among these image variations, as exhibited in Fig. 4 illustrations.


Figure 2: Dataset of various ranges with angles.

The classification of date fruit using this dataset is difficult as demonstrated in Fig. 2, some data types can be easily recognized from one another in terms of type classification based on their outward appearance, while others are challenging to tell apart even by a professional. Figure 3 shows how date bunches of the same variety can differ greatly regarding ripeness level, brilliance, seizing state, scale, and angle. Dates growing in huge clusters (bunches) made it difficult to classify their maturity because the dates in one bunch do not all reach maturity simultaneously. Dates can also be harvested at overlapping maturity stages, as seen in Fig. 4. This makes it challenging for experts to categorize or label them. Classifying people according to their maturity is challenging because of many environmental factors.


Figure 3: Levels of date maturity.

An Intel Core (TM) i5 processor with a 3.60 GHz core frequency, 8 GB of RAM, and an NVIDIA RTX 3060 GPU were used to train the detection model. We additionally employ Python 3.9.0, Pycharm serves as the compilation script, Torchvision 0.4.0, and a Cuda-compatible streamlet framework (v11.2) have been employed for training.

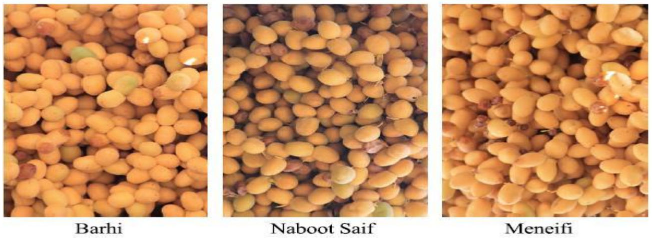

Figure 4: Illustration images to differentiate.

Figure 5: Individuals at different maturity levels of dates bunches.

The lack of readily available roadside data, mainly if we are absorbed in identifying them in punitive and unadorned weather conditions, is one of the difficult problems in vehicle recognition research. Data augmentation is one method for overcoming this obstacle because it enables researchers to significantly increase the range of roadside environmental conditions, as shown in Fig. 5. The dataset was expanded using the following methods.

To allow the model to account for various colour arrangements for substances and sections in participation images, this augmentation technique randomly modifies the colour levels in an image. The colour level for the photos in our collection was fixed between 8° and +82°.

Figure 6: Palm dates Hue contrast.

Inundation growth alters how colourful and vivacious the image seems, much like hue augmentation does see Fig. 6. We added 50% saturation to the dataset. Saturation augmentation alters how colourful and vibrant the image seems, much like hue augmentation does. We added 50% saturation to the dataset see Fig. 7.

Figure 7: Palm dates saturation contrast.

We increased the picture brightness variability up to 75% to

make your brand more resilient to changes in illumination and camera settings.

Figure 8: Palm dates exposure contrast.

The brightness and exposure settings often have the same effects see Fig. 8. However, although brightness has no partiality and affects all qualities likewise, revelation favours highlight tones more. We increase exposure by between -30 and +30 see Fig. 9.

Figure 9: Palm dates exposure contrast.

The size of the training dataset is essentially increased by introducing noise see Fig. 10. The input variables are altered arbitrarily each time a training sample is introduced to the model, making each exposure to the model unique. This makes adding noise to input samples a straightforward data augmentation method.

Figure 10: Palm dates noise contrast.

We describe our strategy in the following part, using YOLOv4 as the foundational architecture. The model processing frame rate and cutting-edge precision is what accounts for this. With an estimated implication rapidity of 65 FPS on top of the Tesla V100, the MS COCO achieves an precision of 43.5% AP (65.7% AP50).

We have used this language for the front and rear ends. The back end refers to machine learning, data transmission to the model, and obtaining the accuracy of automobile dent detection This product's functionality will be offered in this way because it is entirely software-based. Software. Since our solution is entirely built on deep learning, as stated in this paper, there are models that we have. The vehicle will be categorized by width, height, and color. The use of a single-stage deep learning model for wrong-way identification of vehicles. The backend architecture was a deep learning model. We used the photographs to train a machine, and we then imported the dataset into Jupiter Notebook to test the technique. The CNN method attempted to equate three aspects of a photograph—color, positioning, and color structure—against a photograph that is continually based on dots and uses an RGB color scheme (red, green, blue) These features are exported by CNN to perform. Grayscale photos can be supplied, and the binary output is also available. ReLU (rectified linear unit) layers, convolution layers the lowest interconnected bits of bitmap graphics are combined to create a fully connected neural network image, yet each dot does have a pliability that is predictable as the image pixels. When we examine a digital image, it often has three color components, such as the RGB frequencies and "RGB" values.

IV. RESULTS

Images were separated into a training, validation, and testing set, as shown in Fig. 11 and 12 of the split was used for drill, 15% for the support set, and 15% for analysis. Figure 12 shows how many photos and instances of cars there are in our Augmented custom dataset. During the experiment, it was found that custom data set's training loss was rather substantial. However, the size of the data set over expansion and refinement reduced the loss curve.

V. CONCLUSION

A deep learning-based real-time machine vision system has been presented for harvesting date fruit with a UAV in an orchard setting. The framework used to categorize date fruit groups based on sort, ripeness, and reaping method consisted of three models. With no-tuning, transfer learning was employed for the categorization tasks. We looked at YOLOv4-specific pre-trained models for one stage. We created a trustworthy machine vision system using an extensive image collection of diverse date types at every stage of development. To imitate the trials in natural situations and date fruit farms, a large variety of data points were used to generate the dataset. The suggested technique generated great classification accuracy and a high classification rate on this challenging dataset.

Our upcoming study will expand the dataset by including test photographs obtained from several date orchards. We will also investigate more modern YOLOv8 models to reduce memory usage and computational complexity.

Figure 11: Palm dates saturation contrast.

Figure 12: Palm dates saturation contrast.

FUNDING STATEMENT

The authors declare they have no conflicts of interest to report regarding the present study.

CONFLICT OF INTEREST

The Authors declare that they have no conflicts of interest to report regarding the present study.

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